Incentive-based Demand Response: A rebate-based Design

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***Abstract*—In future power grids, the high penetration with Renewable Energy Resources (RES) will be a big challenge. The problem is not the high RES contribution per se, but even desirable in order to make a decisive contribution to climate protection through CO2-neutral power generation. The problem lies in particular in the fact that power stations based on fossil fuels in current electricity networks are stabilizing factors and sources of operational flexibility. In future electricity grids, new sources of flexibility must be tapped - not only at the generation but also on the side of demand, e.g. through Demand Side Management (DSM). Various approaches are divided into direct and indirect control methods. In this paper, we present a model class of Incentive-based Demand Response (IbDR), where the power consumption of household coalitions is indirectly controlled by rebates on electricity bills. We apply the theory of (convex) cooperative games to design IbDR events that promote cooperative behavior of households. In particular, the methods are designed so that the use of storage (batteries) are very beneficially integrated. We have developed a simulation tool MASim that simulates electricity consumptions of households. Using MASim we carried out numerical experiments, which show the functionality of our proposed IbDR method. In field studies, we developed the ICT and tried out how batteries can be controlled within the scope of our proposed IbDR schemes.**

***Index Terms*—Demand-side Management, DR-events, Batteries, Cooperative Game Theory**

I. Introduction

In traditional power grids, uncertainty is mainly based on fluctuations in energy demand. Statistical and econometric methods as well as predefined load profiles are used to reconcile the operational planning of bulk production (generation schedules of power plants) with the loads. This balancing is generally done relatively early (day ahead or earlier) and grid constraints are usually negated. Subsequently, the Transmission Service Operators (TSO) try to avoid any congestions in the transmission grids - for example by re-dispatch - usually also day-ahead. In the short term - 15 minutes to a few seconds before real time - any irregularities are repaired by (expensive) control reserves (Frequency Restoration Reserves (FRR), Frequency Containment Reserves (FCR)). Often, FRR / FCR services (e.g. spinning reserves) are provided by power plants (nuclear, coal, gas, hydro power station) that are also responsible for bulk power production.

The big challenge in future electricity grids is the significant penetration of Renewable Energy Resources (RES) (wind power, photo-voltaic etc.). Distributed renewable energy sources will replace - at least partly - bulk production and - hence - important stabilization factors of power grids are reduced (like sources for control reserves). Additionally, different to traditional bulk production, wind power and photovoltaics cause a lot more uncertainty in the power grids. And it should not to be underestimated that RES generation happens mainly in small and medium-size units, which no longer feed the produced power directly into a TSO grid, but do so in the Distribution Service Operators (DSO) grids. TSOs will not longer be able to synchronize with a few power producers, but will face a huge number of them; most of them not directly linked to their grids. Consequently, it is up to the DSO not to rely primarily on the TSOs to stabilize distribution grids, but this task will be - at least partially - the responsibility of DSOs. Clearly, it will exceed the capabilities of a DSO to perform FCR / FRR actions; these should remain the responsibility of the TSOs. It must be the task of the DSOs to avoid the need for frequency control measures as much as possible; and this also by intraday actions, and - important - considering grid contraints. But DSOs need flexibility services for this. EU Smart Grid Coordination Group (Smart Grid Conceptual Model) writes ([1], page 84, l530ff): "Flexibility, thus, will be key. Where until

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today in the current supply follows demand model, flexibility was offered in bulk generation, in the future in the demand follows supply model the flexibility must be equivalent offered on both sides (generation (centralized and decentralized) and consumption (e.g. demand side management))." The main goal in this paper is to design and simulate a DSM model class where it is beneficial for many households to cluster and to be represented by a market aggregator. An important part is the utilization of (battery) storage in order to support significantly households' and cluster's DSM efforts.

If our society pursues the goal of a clean, CO2-neutral, sustainable energy supply, it has to face these challenges. In contrast to traditional power grids, smart grids are designed to allow substantial information exchanges in any direction, and provide tools like smart metering, advanced ICT, etc. needed in power systems for integrated energy management and decentralized autonomous grid control. EU Smart Grid Coordination Group states further ([1], page 84, l535ff): "Therefore the ICT infrastructure and ICT solutions, which enables the required flexibility on demand and supply side in a fully interchangeable way, becomes a key component of the smart grid and therefore it will be become part of the smart grid eco system."

In a conservative approach, power consumers (like households) allow external control of (at least some of) their consumption. Bigger loads with little to no impact on comfort and no direct user interaction are obviously most suitable. For example, heating and cooling units can be switched on and off at any time as long as the tempearture is kept within predefined bounds (see [2]). Overnight charging of an electric vehicle can be delayed or done with limited current, given that the battery is fully charged when the owner wants to use the vehicle in the morning. Likewise a washing machine might be not started immediately (confer [3]). Other appliances like a stove or a TV set can definitely not be controlled from an external entity.

In the simplest case, electricity suppliers try to operate households' devices within given constraints (like minimal and maximal room temperature) or suppliers incorporate households' (comfort) optimization into their control decisions. In more sophisticated transactive control approaches (see [4]) not a supplier controls households' devices but the system itself controls appliances by contingent interactions between the components of the system and by continuing adaption in order to maximize suppliers' profits, respectively minimize households' costs.

However, in many cases it is not expected or even not desired that someone else controls consumers' devices. Then, electricity suppliers have to rely on the cooperation of the power consumers in order to carry out a meaningful DSM. Of course, a powerful tool is pricing, like Time of Use (ToU) pricing. Suppliers' other instruments can be offering rewards and incentives, or just better understanding households' preferences.

Instead of controlling electricity consumers, their supplier rely – in combination with pricing, incentives, and rewards – on market mechanism. Assuming rational agents, the participants of the power grid implement decisions that guarantee them the best possible outcome. Mathematical programming and noncooperative game theoretical models of smart power grids allow us to understand the behavior and interactions in these systems; analysis of these models guides us how to make the grid smarter (as an example we want to mention here [5]). The authors in [6] call these approaches direct control methods.

In this paper we focus on indirect control methods; differently to the situation where power consumers implement - as rational agents - an optimal (and thus prescriptive) solution, in this paper we want to investigate smart grid set-ups where the participants of the power grid are not cooked down to a single mathematical model. They are not fixed to prescriptive power consumption rules, but they are allowed to choose any proper (even non-rational) consumption decision. Demand side management is carried out by indirect control methods and a common approach is that power consumption is controlled by means of incentives, confer Incentive-based Demand Response (IbDR); one can find a review about IbDR in [7].

We postulate that electricity consumers can decide which information level on their future electricity consumption (and on the efforts providing it) they agree to provide, and we assume that binding agreements are possible in advance. The energy supplier can give incentives and offer rewards for fulfilling agreements. In principle, the supplier could fix complex individualized contracts with every electrical power consumer, but we consider this hardly practicable. The potential of this approach is fully exploited when acting as a group (coalition) allows improvement compared to the situation when each participant of the power grid acts individually and independently. In a typical setup, a given set of players (power consumers) are grouped around an aggregator (facilitator, mediator), who represents the interests of the group as a whole.

An example is given in Equation (1) in [8], where electricity consumers get compensated for their load level reduction during a single DR event. Moreover, in this paper [8] a more interesting DR scheme is proposed, where DR activities - still load level reductions - are rewarded only, after a minimal level M of a total load level reduction is achieved. A single consumer cannot achieve this minimal level M, and consumers have to group up to coalitions that are big enough to fulfill the minimal load level reduction. It is to mention that in the cited framework, the marginal increase of a reward due to a load level reduction is constant (as long as the minimum level M is fulfilled). The major goal of our paper is to design fair and attractive DR events, where the marginal reward increases the higher the contribution to the DR event is. Especially, we want to design DR events, where support/usage of storage (batteries) makes cooperation more effective.

For the ICT (Information and Communications Technology) of this kind of energy networks, it is important to know how much each member of the group contributes to the group's goal. Especially, after realizing the power consumption of the individual electricity consumers, based on a given and known agreement, the ICT has to compute the group's total achieved reward (value of the coalition) and the players' individual contribution. Based on these figures, the ICT has to calculate and manage an allocation of the reward to the individual power consumers. In a wider perspective, we investigate how to design DR events (or, more general, binding agreements), which are favorable for both, power consumers and their supplier. A crucial question is, how storage (batteries) can be incorporated beneficially into the system, and how ICT has to be designed to in order to be able to carry out these processes automated.

This paper is organized as follows. In Sec. II we describe coalition games and DR schemes in general. In Sec. III we describe how to compute rebates, and in Sec. IV we show how batteries can be integrated to advantage. In Sec. V we present the coalition game set-up used. Then, simulation and results are given in Sec VI. Finally, our conclusion is presented.

II. Coalition Games and DR schemes

We assume that the electricity supplier announces DR events and a group of power consumers led by an aggregator contracts compensation based on their potential DR services. The purpose of setting up a group is that each member achieves the same or better result (i.e., less electricity cost) when following a DR program in a group than in the situation of disagreement where the players are acting individually. Those group members who do not contribute to the agreed DR scheme with their power consumption behavior (dummy or zero players) will not receive an increase in their score and will be unmasked to the aggregator. Group members are not tied to an optimal (prescriptive) solution, however, if consumers are provided with information about their personal outcomes (and, of course, about the DR scheme), there may be a different (more cost-effective) energy consumption behavior in the future. Conceptually, in this article we discuss model approaches from the field of coalition games; an introductory chapter can be found in [9].

Additionally, we model batteries as supplementary players operating in an effective DR response. Coalition games will make sense only, if grouping improves effectiveness: the higher the group's contribution to the DR scheme is, the more effectively batteries can be used. This approach is applied for valuating the alternatives, if a group of consumers considers to purchase batteries. Using regret matching [10], respectively joint strategy fictitious play [11], individual consumer's decisions about holding shares of a joint battery (operated at the aggregator's level) are contemplated.

Mathematics of DR schemes

We consider a sizeable group of n (electricity) consumers who have gathered around an aggregator for a given DR scheme. Consumers may only join or leave the group at the beginning of a planning period. We assume that the DR scheme is designed so that the system's ICT, after realizing consumers' power consumption, can calculate the total payoff based on DR activities for each subset of these n consumers. In other words, for a given set $N = \{1, \ldots, n\}$ of n consumers, the ICT of the smart grid must be able to calculate the nonnegative value $v(S)$ of any coalition $S \subset N$ (v maps groups of consumers S to the welfare they will achieve $v(S)$, if they act together).

Though in practice, the ICT will never compute totally the so-called characteristic function v of a coalition game (N, v). Therefore, we only consider DR schemes, from which we are able to derive a formula/rule that allows us to compute a quantitative value $v(S)$ of reward gained by the DR activities by the members of any given coalition $S \subseteq N$; especially observed DR activities of the grand coalition (consists of all players in N) results in DR rewards (the reward funded/realized by the supplier) equal to the value of the grand coalition $v(N)$ (here $v(S), S \neq N$ are conceptual values, only). To clarify it, the DR scheme defines the characteristic function v, which can be evaluated after the consumers carried out their actions. Of course ICT has to update – in different planning periods, we face DR activities and, hence, different characteristic function values.

Now let us have a look on a n-person coalition game with given characteristic function v and assume transferable utilities. The latter refers to the concept that a group (coalition) S can distribute the value of its coalition $v(S)$ among its members acting on their own authority. As in a group of family members - although they are selfish to some extend - no one tries to maximize his/her individual utility at other family members' expense, but the family tries to distribute in a fair (i.e. stable) way. The set of feasible solutions of a coalition game (N, v) consists of all utility allocations for the whole group N, where the value of the grand coalition $v(N)$ is distributed fully among the players and every player of the game gets a non-negative share of $v(N)$ allocated.

Of course an allocation where one player gets the full value of the grand coalition allocated is feasible, but such an allocation may not be stable in the sense that other players may feel harassed and decide to leave the grand coalition and seek to build on their advantages in smaller coalitions. In this sense, a feasible utility allocation is called stable, if the value of the grand coalition is fully allocated among all players of the game and the aggregated allocations of the players of any potential coalition S is greater equal than the value of this coalition, $v(S)$. In other words, no coalition can provide its members a better position than they can achieve joining the grand coalition (coalitionary stable). This is valid for the trivial coalition of a single player, too, which means that a single player's payoff for joining the grand coalition is as least as good as acting individually (individually stable). We call the set of all stable allocations of a coalition game (N, v) the core of this game (see [12]). Unfortunately, there are coalition games, where the core is an empty set; mathematical theory shows us that just in convex (coalition) games the core is never empty.

Whenever in a DR scheme the rewards for DR activities can be quantified, it is possible to compute the characteristic function v for a group of N consumers and consequently we can formulate a coalition game (N, v). However, coalition games with empty core(i.e., without stable solutions) may result. From mathematical theory we know that this can happen only if a DR scheme allows the following situation: consider a coalition S in the absent of a player i. The margina contribution $m^i(S)$ of player i to the coalition S is the difference between the value of the coalition, when player i is added to S, minus the value of the coalition S (without i). Now add one or more players to S (not i) to form a new, bigger coalition T. If now the marginal contribution $m^i(T)$ of player i to the coalition T is smaller than the marginal contribution $m^i(S)$ of i to the coalition S, then it is not possible to find stable utility allocations (the core is empty). However in such a case, we face a DR scheme where building groups is counterproductive and hence modelling by coalition games should be questioned. Coalition games that exclude such (for building coalitions counterproductive) cases are called convex games.

We have discussed that a coalition game (N, v) has to be convex to ensure meaningful (stable) solutions. Keeping this in mind, let us do some reverse engineering for constructing DR events and DR schemes suitable for coalition games. For this purpose, recall that for a convex coalition game the characteristic function v has to be a composition of a convex function f and a measure μ, i.e. $v(S) = f(\mu(S))$ (see [12]). A measure μ is a real valued function that is nonnegative, maps empty set to zero and is additive. In our case, the domain of μ is the set of all coalitions in the game. Obviously, we have to measure DR activities of the members of a coalition (done by μ) and have to transform this measure to monetary values (done by f; subsequently, we will call this function measure-to-money).

III. DR SCHEMES FOR COOPERATION

Knowing the mathematics we have the ingredients to design suitable DR schemes, if the intention is that consumers cooperate. For test scenarios, we assign reference consumption profiles (like baselines in balance groups) to each consumer. The measure of a coalition then is defined by the sum of load level reductions (relative to the reference profiles) of all the participants of the coalition. Results can be summed up over several DR events carried out during a planning period (let us assume a day), e.g. one event in the morning and one event at the afternoon peak.

Based on measured DR event contributions of the grand coalition the supplier gives a discount (as a lump sum), applying a strictly convex measure-to-money function f, a mapping of group's aggregated DR event contribution into monetary values (defining the lump sum). In other words, the total load level reduction of the group is calculated and the supplier gives a discount on the group's (not individual) cost of service; the marginal discount increases with the increase in load level reduction.

This reward is given to the aggregator and equals the value of the grand coalition. While every member of the group pays for its actual power consumption a given and known flat or variable (time of use ToU) price to the supplier, the aggregator distributes the reward among the group members according to their contribution to the DR scheme.

A. Computation of the Individual Rewards

As we construct a convex game for the distribution of the reward, the existence of stable allocations can be concluded. However in general, stable allocations are not unique. Shapley proposed in [13] an allocation that is the unique allocation fulfilling efficiency (value of grand coalition is fully distributed), symmetry (two player who play the same strategies are rewarded equally), dummy player (those who do not contribute are not rewarded), and linearity (the sum of rewards of two DR events equals to the reward if the DR events are carried out jointly in a DR scheme); this unique allocation is called *Shapley values* and can be computed for any coalition game (N, v).

For the formula to compute Shapley values see, for instance, [8], Equation (5). Shapley values are unique and - theoretically - they can be computed for any coalition game. However, keeping in mind prior considerations it is obvious that this allocation is not necessarily stable for nonconvex coalition games, but it is well-known that this allocation is stable for (in the core of) convex coalition games.

Looking more carefully at the formula for the Shapley values we realize that computing and adding together all its summands is practically not possible in the presence of about more than 20 players (due to complexity issues). Shapley had proposed to add a limited number of randomly chosen summands (Monte Carlo method). In the topical publication [8], the authors propose a statistical sampling method that tries to minimize possible deviation from the computed mean value for the Shapley values given an upper limit of computed summands.

Smart grids' ICT handles the reference profiles of the consumers, holds and distributes the exact definition of reward calculation (DR scheme characteristics), executes these calculations (including the distribution of rewards) and does all the accounting between supplier and aggregator and between the aggregator and its consumers. Especially, we implemented the - in the immediately preceding paragraph referenced - algorithm for computing the Shapley values and integrated it to the ICT.

IV. DR SCHEMES FOR STORAGE

Storage will play a significant role in future power grids; especially for providing flexibility. Obviously, it requires a powerful ICT system to integrate e.g. batteries and control them in an optimal way.

In the simplest scenario, a battery is discharged at its maximum rate during peak periods with high energy price (in case of ToU pricing) and then charged during off-peak periods when energy is cheap (arbitrage energy trading with batteries). This usage is feasible when the price difference between peak periods and off-peak periods is large enough to make up for the cost of the battery. The requirements for the ICT system are simple. Usually time and duration of high and low price periods are known in advance, and the ICT just needs to configure the Battery Management System (BMS) accordingly. The BMS then triggers charging and discharging so that it fits the batteries characteristics optimally.

In more complex DR events, a battery can be used to change a groups consumption so that it follows a desired/advantageous pattern. For example, a battery is discharged in a way that overall consumption stays below a agreed threshold. Another use case might be shifting power consumption so that the usage of renewable energy sources is maximized. These scenarios require a much deeper integration of battery control into the system.

In order to utilize batteries optimally the BMS needs a lot of information about the battery, e.g., the type of the battery, state of charge (SoC), state of health (SoH), maximum rampage rates, charge and discharge currents or internal temperature. These parameters impose restrictions on how the battery can be operated, e.g., exceeding the internal temperature limit can permanently damage the battery. On the other hand, keeping operating conditions within certain parameters can significantly reduce the wear of some battery types and thus increase their lifespan. For such a deep integration the BMS must not be limited to reading battery parameters and switching it on and off but has to be able to control the rate of charge and discharge as well.

Obviously to take full advantage of a very sophisticated BMS a more capable ICT is required. The communicational and computational requirements obviously increase with the amount of data that has to be processed. As mentioned before, in the most basic scenario either predefined times or simple trigger signals are sufficient to discharge and charge the battery and billing can be done by recording the SoC or currents and timestamps. In order to realize complex DR events the ICT probably has to react on changes of a group's consumption in real time.

For batteries, we extend the game theoretic setup described above. Batteries here are treated as additional players $n+1, n+2, \ldots$. For the discussion here let us assume that we add a single battery. On the one hand, this battery operates as an optimized consumer (charges during off-peak hours, discharges during peak hour DR events), on the other hand - differently to consumers - we have to incorporate the (fixed and variable) costs of the player-battery to the coalition game. Especially modeling how the battery contributes to the value of a coalition that includes the battery is of interest. We can add easily the contribution of a player-battery to a coalition to the measure μ, which does not change qualitatively the structure of measure μ. Clearly, we can apply a measure-to-monetary-value function f to this adapted measure. We incorporate cost for operating batteries (efficiency losses). We neglect investment cost for batteries; if we did incorporate them, the solution would be never use a battery, as the cost per kWh stored is 30 Eurocent and higher - up to 60 Cent per kWh in case of environmentally friendly batteries that are based on salt-water technologies.

However, we have focused on DR schemes that places emphasis on utilisation of batteries. As we have learned the value of a coalition should increase progressively with the increase of the scale of coalitions. The marginal reward of a contributed kWh of a battery should increase, if more DR active players join the coalition. In our studies (confer Section V) we design and investigate a rebate-based measure-to-money function f to constitute this.

A. *Multi-Agent Simulator (MASim)*

To analyze the effectiveness of mechanisms like incentives and the resulting behavior we developed a Multi-Agent Simulator (MASim). It is a discrete event simulation framework where agents can interact with the environment (and each other) at given times. Two types of agents, namely Aggregators and Households, were implemented. The aggregator manages the battery and triggers DR events.

Households have residents who can be asleep, awake and not at home. Residents have slightly different behaviors like when they get up in the morning and go to bed at night or if they are at home during the day. Devices in the household consume energy and are switched on or off based on a predefined schedule, by residents or with DR events. We implemented the following types of devices:

1) constantly consuming energy and cannot be switched off,
2) can be switched on at any time and then need to run for a certain amount of time (e.g., a dish washer)
3) can be switched on and off at any time by residents or DR events.

Usage patterns influence the way devices are used. They can be arbitrarily complex but the current implementation switches devices on or off randomly where the probability depends on the state of the environment like the time of day, state of the residents, or the current energy price. For example, a stove is most likely used at noon or in the evening, but only when someone is at home.

Additionally the environment holds information about the global surroundings of the agents, e.g., energy prices or weather/temperature, which can affect the usage patterns of devices. A heat pump for example is only needed below a certain temperature.

A simulation configuration includes the number of households, their residents and devices, size and type of the battery, energy prices and parameters for DR events as well as the duration and granularity of the simulation run.

The simulation loops through the following steps:

1) Update the environment (time, temperature)
2) Update the residents states
3) Switch devices on or off based on their usage profiles
4) Households send their current consumption to the aggregator.
5) The aggregator calculates the energy costs and rewards for each household and sends them out.
6) The aggregator triggers a DR event if it is required to keep the overall consumption within agreed bounds.

In our case studies, partly carried out in reality, we have used a RedFlow zinc-bromine battery for analyzing the physical aspects of battery management. The Battery Management System offers a serial Modbus interface to query all operating parameters and trigger charging or discharging. The battery is connected to a power inverter which is able to regulate the charge and discharge rates and can be controlled via Modbus as well. This analysis allows also a deeper understanding of the demands on the ICT for controling a system of an aggregator, batteries and the related electricity consumers.

V. Rebate-based Design for a DR Event

Validation at the component level has shown that the brand-new algorithm to compute the allocations (Shapley values) proposed in [8] works fine, and simulating households' electricity consumption and contributions to DR event with our developed MAS simulation MASim works fine, too. The aggregated electricity consumption of a big number of household is smooth, however, consumption of individual households is to a high degree fluctuating. It may happen that in one period cook-top, microwave, oven, hand blender, and dish washer are used and therefore household's electricity consumption is beyond predefined limits, but over a longer period the averaged consumption of the household stays clear within the limits. If a household consumes more than prearranged, then $\mu(.)$ is no longer a measure, hence $v(.)$ is no longer the characteristic function of a convex coalition game; finally, negative allocations (penalties) can occur. At the first attempt, we put the Shapley Value, hence the allocation of the household, equal to 0 instead of a negative value, which is a penalty).

Discussing this more thoroughly, it should be clear that the load level reduction X_i of a household i is relative to its (known, given) base line consumption B_i. However, one question is how the base line can be defined. Based on historical data? Based on the predefined patterns (Standardlastprofil)? Based on a negotiated contract between aggregator and supplier? Anyway, in reality sometimes households will violate these limits; in some kind, they contribute negatively to the DR event (and such behavior results not from a wrong design of our simulation tool). In a first attempt in such cases, we put the allocation to zero (aware that allocations of the contributing households are reduced), in the further analysis we operated batteries (owned/installed at the households) to compensate electricity consumption higher than the given base line. In this way, battery utilization was crucial to stabilize the system.

In this study, we operate batteries at the households (individual use) and batteries aggregator (common use). Physically, these batteries need not be installed according their utilization; for instance, household can own shares from a central battery at the aggregator, and this share is reserved for individual use. The modeling difference is the utilization, individually or commonly. In the latter case, we analyze especially smart grid business models, where the batteries' main purpose is to support the success in a DR event. There are several different setups for DR event contribution (like load shifting or shaving, electricity consumption following a predefined consumption pattern as closely as possible); in this study, we take load shifting as DR event as the base.

A. Design of DR Events

The difference between the base consumption B_i and the realized consumption $\bar{X}_i$ measures the contribution $X_i = B_i - \bar{X}_i$ of an individual household i to the DR event. Of course, incentives can be given, for instance, proportionally to the collective contribution of all households $q\,\mu(N)$; hence the measure-to-money function would be linear with coefficient q. In this study, we modeled a rebate $r(\mu(N))$ on the actual aggregator's electricity bill (that are the aggregated bills $\sum_{i\in N} \bar{X}_i$ of the members of the grand coalition N) during the DR event period and carried back the rebate to the real consumption $\bar{X}_i$ of individual households:

$$f(\mu(N)) \quad = \quad r(\mu(N)) \sum_{i\in N} \bar{X}_i. \tag{1}$$

where μ measures the households' DR-event contribution

$$\mu(N) = \sum_{i\in N} X_i.$$

We have chosen the rebate function $r(.)$ in a way that the marginal rebate increases with an increase of the households' DR event contribution μ. If households contribute more to the DR event, their consumption decreases and, hence, there is a tendency to reduce the DR event discount. However, we have designed the rebate in a way so that this effect is (more than) compensated. Moreover, we define the rebate such that measure-to-money function f is convex and consequently the coalition game is convex (recall $X_i = B_i - \bar{X}_i$:

$$f(\mu(N)) \quad = \quad \left(\frac{2\mu(N)}{\sum_{i\in N} B_i}\right)^3 \left(\sum_{i\in N} B_i - \mu(N)\right) \tag{2}$$

Note that if the aggregated DR event contribution is more than approx. 50% of the base consumption $\sum_{i\in N} B_i$, this setup does not longer work; a further shifting/saving of electricity use will decrease the reward. We have chosen the value of 50% arbitrarily; however, this value can be adapted by changing parameters in the rebate function $r(\mu) = \left(\frac{2\,\mu}{\sum_{i\in N} B_i}\right)^3$ (note that factor 2 and power 3 define this 50%).

In case of sub-coalitions $S \subsetneq N$, we have to adapt the (now theoretical) reward for this group to the aggregated consumption of the grand coalition $\sum_{i\in N} B_i$:

$$f(\mu(S)) \quad = \quad \left(\frac{2\mu(S)}{\sum_{i\in N} B_i}\right)^3 \left(\sum_{i\in N} B_i - \mu(S)\right) \tag{3}$$

This modeling worked as long as no households violates the base line consumption. At the point, when we put Shapley values for households, which thwart the DR event, to zero (practically eliminating them from the group), $\sum_{i\in N} B_i$ represents no longer correctly the grand coalition (N is changed).

Finally, we have adapted the measure-to-money function (concentrate at the index set of the sum)

$$\begin{aligned} f(\mu(S)) &= \left(\frac{2\mu(S)}{\sum_{i\in N} B_i}\right)^3 \left(\sum_{i\in S} B_i - \mu(S)\right) \\ &= \left(\frac{2\mu(S)}{\sum_{i\in N} B_i}\right)^3 \sum_{i\in S} \bar{X}_i. \end{aligned} \tag{4}$$

Now we have in the reward function for coalition S the consumption of this group and not more. Not replacing the constant aggregated base consumption $\sum_{i\in N} B_i$ in the rebate function makes sense as this is the negotiated value between aggregator and supplier and is based on the initial participating households.

We have to be careful, as $\sum_{i\in S} B_i$ in $f(\mu(S))$ depends on S and cannot be a parameter (constant) any longer. We face now the already explained measures μ and another measure $\bar{\mu}(S) = \sum_{i\in S} \tilde{X}_i$; the measures-to-money function f is now a mapping from $I\!R^2 \to I\!R$ and $v(S) = f(\mu(S), \bar{\mu}(S))$. To ensure that (N, v) is a convex game it is no longer sufficient that f is convex but f has to be directionally convex (confer [14]). In case that a measures-to-money function f is C^2 (twice differentiable) it holds: f is directionally convex iff all second derivatives of f are non-negative; the updated f mentioned in (4) fulfills this.

VI. Simulation Runs

Next we want to add representative results from our analysis (done with our developed MASim):

Fig. 1 shows the influence of home-batteries on the reward during a DR event on above mentioned rebate basis under the assumption that 50 out of 100 households participate actively (that is in the MASim set-up they reduce the probability of using household devices during the DR event). The second 50 households in Fig. 1 do not react to the DR event (the probability of using household devices is unchanged). We simulated participation at the DR event by lower probabilities for switching on electrical devices. If a household consumes more than the baseline consumption, (only) household's battery is used to compensate this overuse, as long as a battery is available and it is not fully discharged.

Red dots show the rewards for households without a battery and black ones represent the reward when every household is endowed with a 2,2kW battery (used for its own supply, only). Diurnal electricity costs (including heating and hot water) are about 3,5 Euro, and rewards are up to 35 Euro Cent (ten percent) of household's electricity costs. Active participation at the DR event results in a much higher reward (compare 50 households left with 50 households to the right), and utilizing battery storage increases these rewards (compare black and red curve); especially, households that are not willing or able to contribute actively to the DR event, can use battery storage effectively (compare households 51-100).

Fig. 2 shows the influence of a community owned battery of a larger scale on the reward during a DR event on above

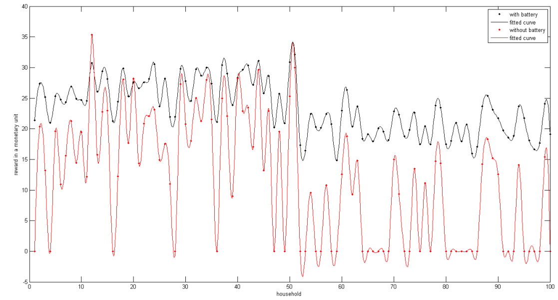

Fig. 1. The figure shows the reward for 100 households, where the first 50 households participate actively at the rebate DR event. The red dots (lower curve) show the simulated rewards in the set-up, where none of the households owns a battery; the black dots (upper curve) show the simulated rewards in the set-up, where we endow every household with a battery with 2,2 kW capacity available. (We have interpolated curves with the intention to make the results better distinguishable, but these curves do not have any meaning.)

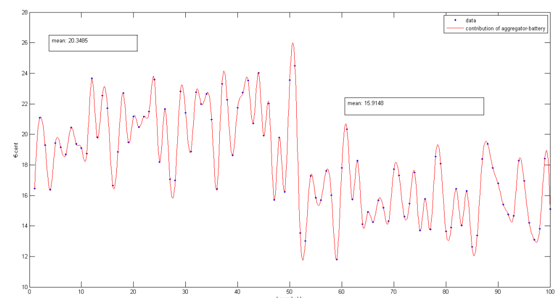

Fig. 2. The figure shows the reward for 100 households, where the first 50 households participate actively at the rebate DR event. A community owned battery with 110kW is utilized to reduce aggregated electricity demand of all 100 households during the DR event (this battery is not individually used). (The red dots show the simulated rewards; we have interpolated curves with the intention to make the results better distinguishable, but these curves do not have any meaning.)

mentioned rebate basis under the assumption that the first 50 households participate actively. The 50 households on the right hand side in Fig. 2 do not react to the DR event, however, electricity demand saved by utilization of the community owned battery is split evenly to the households. Hence, all households receive rewards, although, rewards of households participating actively at the DR event are higher.

Fig. 3 shows shows the effects of learning on the rebate-based DR event. At the beginning, just 10 households actively participate in the DR event. The DR event is mainly carried by a larger community battery (90 kW) and many small batteries (2.2 kW) owned by households.The green dots (interpolated by the lower curve) indicate the rewards for each household. Even the first 10 households actively participating in the DR event receive hardly any appreciably higher rewards compared to the rewards of the other households. We have incorporated "learning" into the simulation by overriding the probabilities of turning on household appliances using a meta-rule. We only allowed reducing the probabilities - so a household that is

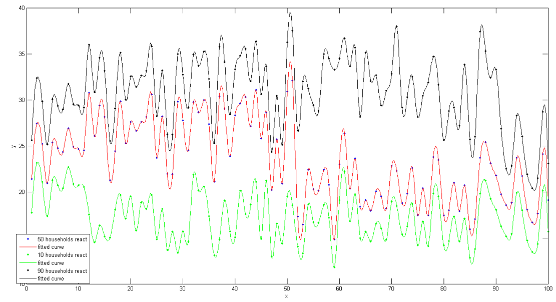

Fig. 3. The figure shows the reward for 100 households during a learning process. A community owned battery with 90kW is utilized to reduce aggregated electricity demand of all 100 households during the DR event and we endow every household with a battery with 2,2 kW capacity available. At the beginning only a few households participate (green; lower curve), more and more households learn to participate (red), and finally 90 household contribute actively to the DR event (black; upper curve). (The red, green, and black dots show the simulated rewards; we have interpolated curves with the intention to make the results better distinguishable, but these curves do not have any meaning.)

already actively participating in the DR event will always do so. Households that are not yet participating are motivated by the enthusiasm of the already active neighboring households, but more likely by paying off (word of mouth) higher rewards to DR-event active households. The first effect mapped in the meta-rule causes a slow increase of the active participants, the latter effect - if then already a larger number actively participates - causes a faster increase, until a certain saturation occurs. If then already 50 households participate, then they receive already clearly higher rewards (middle, red curve). But even households that do not participate actively in the DR event will profit - albeit to a lesser extent. Now that 90 out of the 100 households are DR-event-active, households can expect to receive for their decision to participate actively to the DR-event a 50% higher reward (upper black curve) than in the situation they and 50 other households have not yet participated. But the first 50 households are also benefiting from the fact that another 40 households have now been able to actively contribute to the rebate-based DR event.

VII. Conclusion

In our present research, we investigate possible frameworks for the adaptive behavior of power consumers and corresponding DSM models in combination with (battery) storage. We put a major emphasis on the integration of storage as an integral part in DR schemes. We explore the performance and quality of our proposed DR-models in an agent-based simulation tool MASim that we have developed for test purpose. Finally we have conducted simulation runs with adaptive/learning features, in order to experiment with our rebate DR event design behavior in case of recurring application (e.g. diffusion of reward information).

Performing various scenarios in multi-agent based simulations helps to understand the principle behind the emergence of successful DSM based on the adaptive behavior of consumer agents coupled with memory (battery) usage. We have seen rebate-based DR schemes work well, especially in combination with battery storage. Batteries can be modeled as supplementary players operating in an effective DR response. Of course, since coalition games only make sense if the grouping improves effectiveness, the higher the group's contribution to the DR scheme, the more effectively the battery can be used.

In an adaptive, cooperative design of a smart grid, ICT has to provide a lot more functionality than accounting and billing of consumed electricity. ICT has to maintain DR events (and more general DR schemes), in a more automated, transactive set-up ICT has even to initiate and to shape DR events; of course in any case, ICT has to provide full information about DR events. ICT has, on the one hand, to monitor the contribution of the individual electricity consumers to the DR events, on the other hand it has to trace the (ill) success of the whole group regarding to the DR events. ICT has to compute the allocation of the rewards of successful DR events to the consumers as incentive to behave according to given DR events. Finally, a crucial functionality of ICT is the integration of storage to the smart grid designed as a MAS. We have traced requirements on the ICT during the simulation runs, although at first only we will operate in reality the integration of storage with an already installed battery.

In follow-up projects, we intend to realize other ICT functionalities discussed in this paper and intend to extend it by additional features (photo voltaic - prosumers, service station for electric vehicles operated by the aggregator and assigned to group members etc.).

References

[1] C.-C.-E. S. G. C. Group. (2012) Smart grid reference architecture. [Online]. Available: http://ec.europa.eu/energy/sites/ener/files/documents/xpert_group1_reference_architecture.pdf

[2] T. Ericson, "Direct load control of residential water heaters," *Energy Policy*, vol. 37, pp. 3592–3512, 2009.

[3] P. Du and N. Lu, "Appliance commitment for household load scheduling." *IEEE Transactions on Smart Grid*, vol. 2, no. 2, pp. 411–419, 2011.

[4] S. Katipamula, D. P. Chassin, D. D. Hatley, R. Pratt, and D. J. Hammerstrom, "Transactive controls: Market-based gridwise controls for building systems," PNNL-15921. Pacific Northwest Natl. Lab. Richland, WA, Tech. Rep., 2006.

[5] L. Gkatzikis, I. Koutsopoulos, and T. Salonidis, "The role of aggregators in smart grid demand response markets," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1247–1257, 2013.

[6] P. H. Divshali, B. Choi, H. Liang, and L. Söder, "Transactive demand side management programs in smart grids with high penetration of evs," *Energies*, vol. 10, p. 1640, 2017.

[7] V. Chrysikou, M. Alamaniotis, and L. H. Tsoukalas, "Incentive based demand response methods in smart electricity grids," *International Journal of Monitoring and Surveillance Technologies Research (IJMSTR)*, vol. 3, no. 4, pp. 62–73, 2015.

[8] G. O'Brien, A. El Gamal, and R. Rajagopal, "Shapley Value Estimation for Compensation of Participants in Demand Response Programs," *IEEE Transactions on Smart Grid*, vol. 6, no. 6, pp. 2837–2844, nov 2015. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=7101858

[9] Y. Shoham and K. Leyton-Brown, *Multiagent Systems: Algorithmic, Game-Theoretic, and Logical Foundations*. New York: Cambridge University Press, 2009.

[10] S. Hart and A. Mas-Colell, "A simple adaptive procedure leading to correlated equilibrium," *Econometrica*, vol. 68, no. 5, pp. 1127–1150, 2000.

[11] J. R. Marden, G. Arslan, and J. S. Shamma, "Joint Strategy Fictitious Play With Inertia for Potential Games," *IEEE Transactions on Automatic Control*, vol. 54, no. 2, pp. 208–220, 2009.
[12] L. S. Shapley, "Cores of convex games," *Int. J. Game Theory*, vol. 1, pp. 11–26, 1971.
[13] L. Shapley, "A value for n-person games," *Contribution to the Theory of Games*, vol. 2, pp. 307–317, 1953.
[14] J. M. de Albeniz Salas and C. R. Pallarola, "A note on shapleys convex measure games," Universitat de Barcelona. Espai de Recerca en Economia, Working Papers in Economics 91, 2002. [Online]. Available: https://ideas.repec.org/p/bar/bedcje/200291.html